

# Update on $H \rightarrow bb/cc/gg$ at 350 GeV

CLICdp Analysis Meeting - 6 June 2015

Marco Szalay



Max-Planck-Institut für Physik  
(Werner-Heisenberg-Institut)



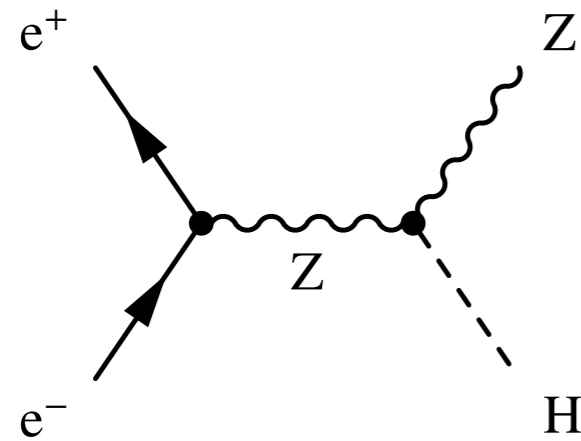
# Outline

- Introduction
- Event selection and MVA performance
- Template Fit Status
- Background modelization
- Conclusion

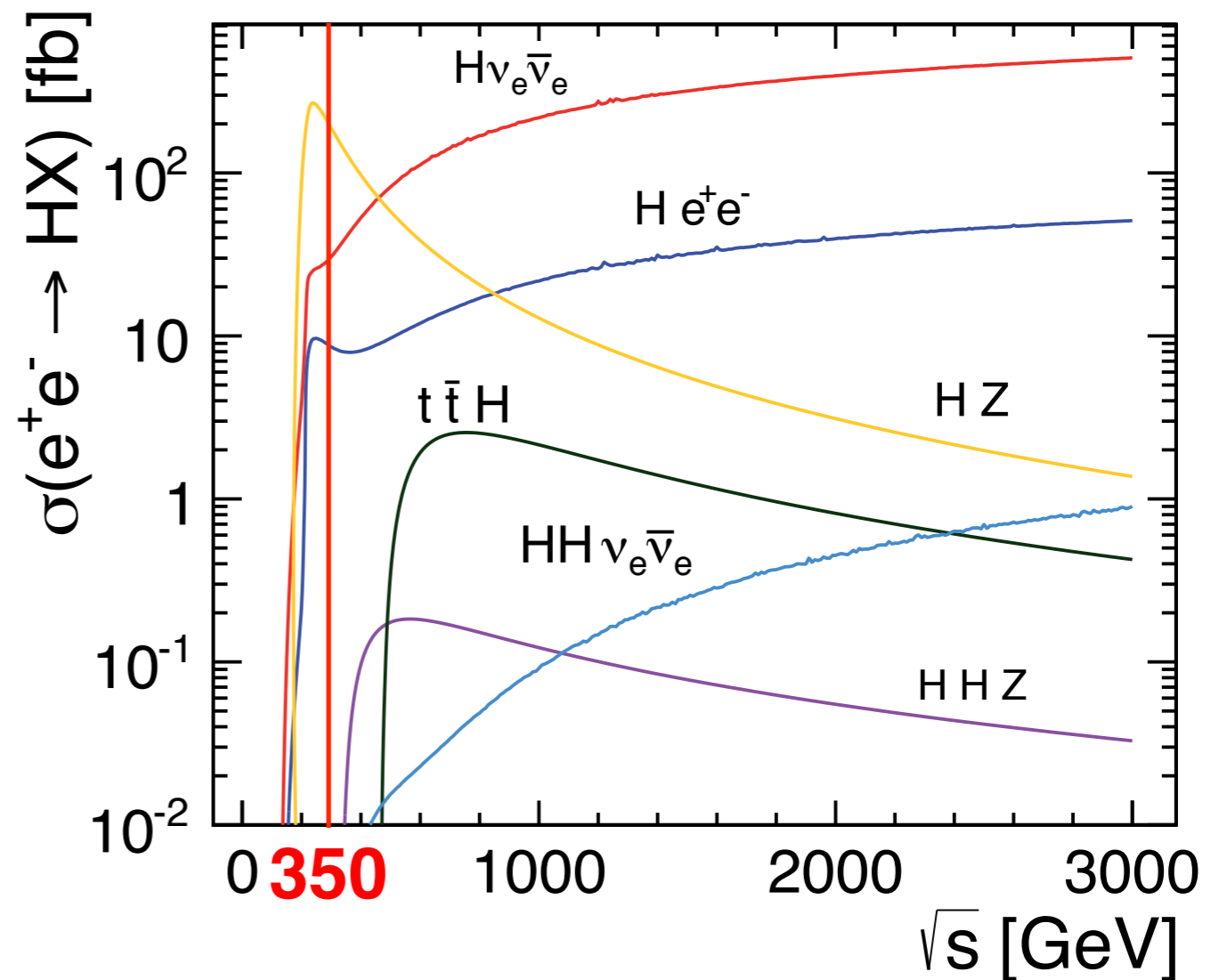
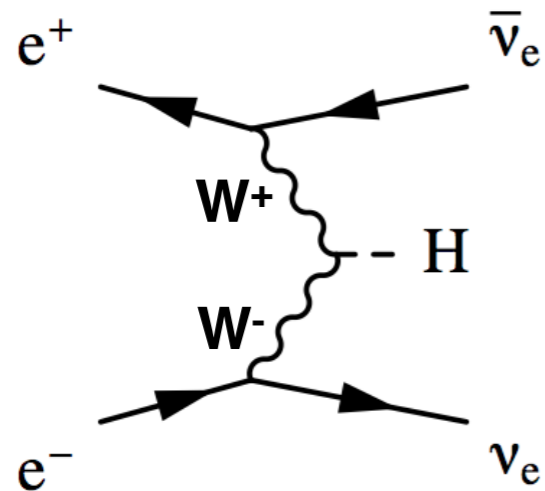
# Introduction

Main H production channels at 350 GeV:

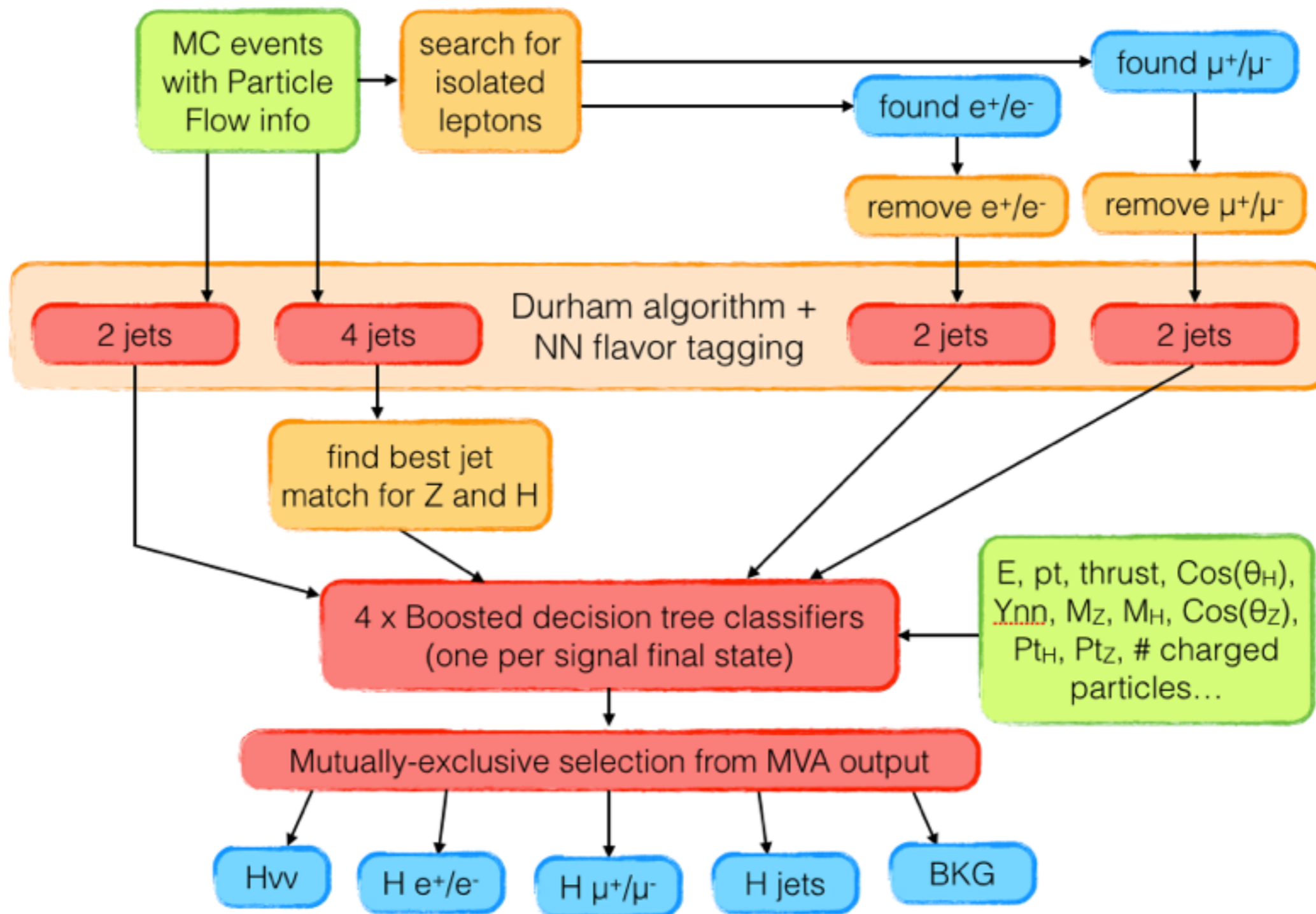
- Higgs strahlung



- Vector Boson Fusion



# Event Selection



# BDT Performance

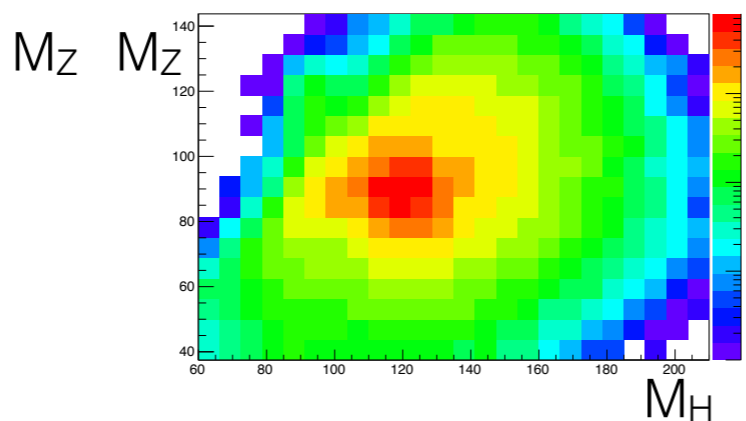
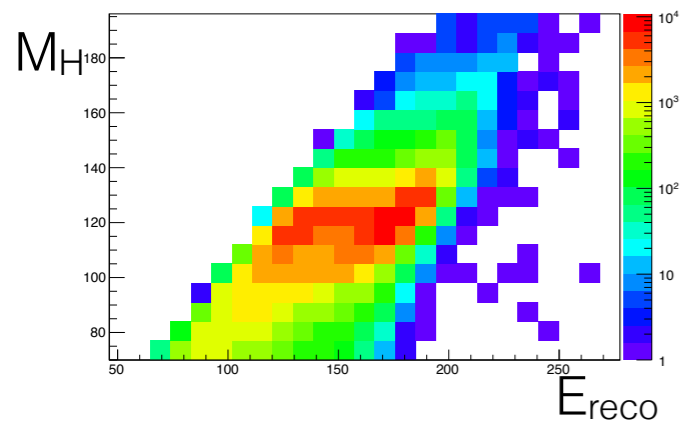
## Preselection:

$H\nu\nu$

- $80 < M_H < 180$
- $60 < E_{\text{reco}} < 260$

$HZ: Z \rightarrow \text{jets}$

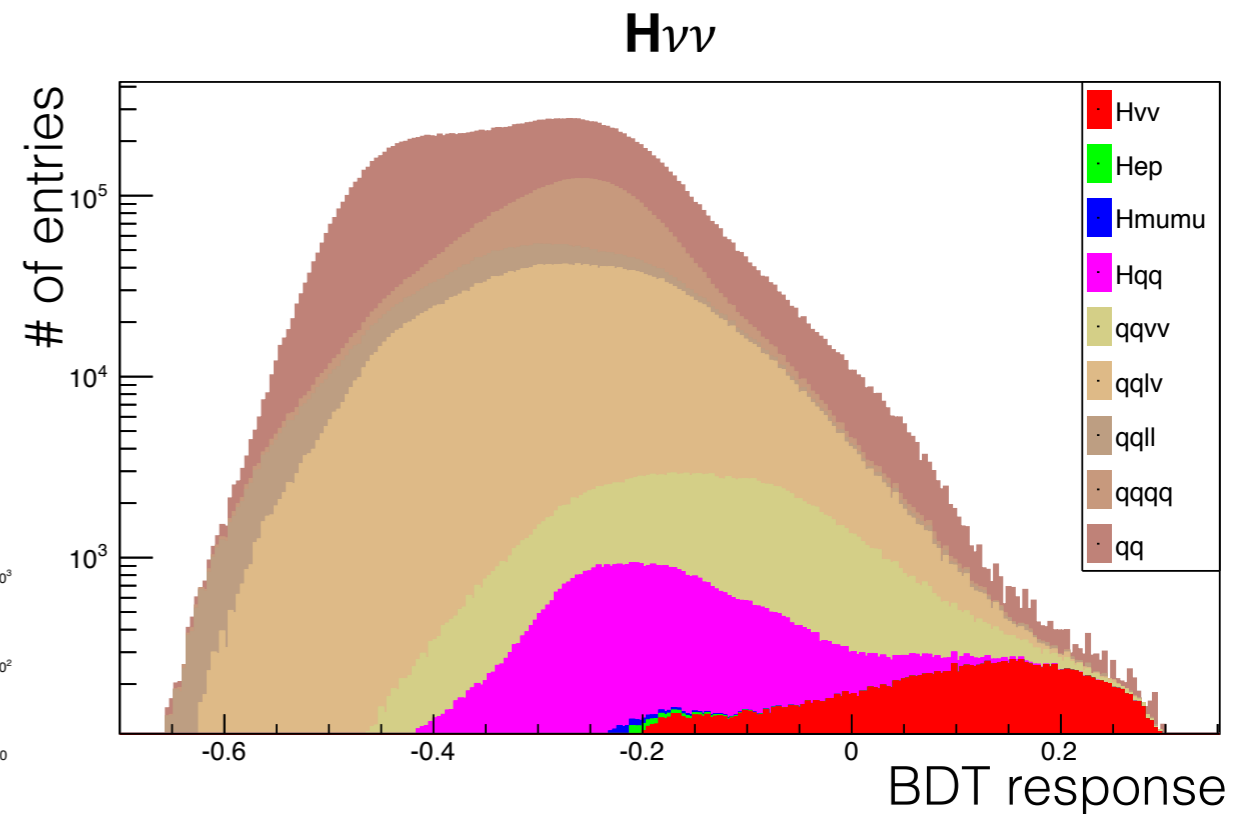
- $70 < M_H < 200$
- $50 < M_Z < 130$



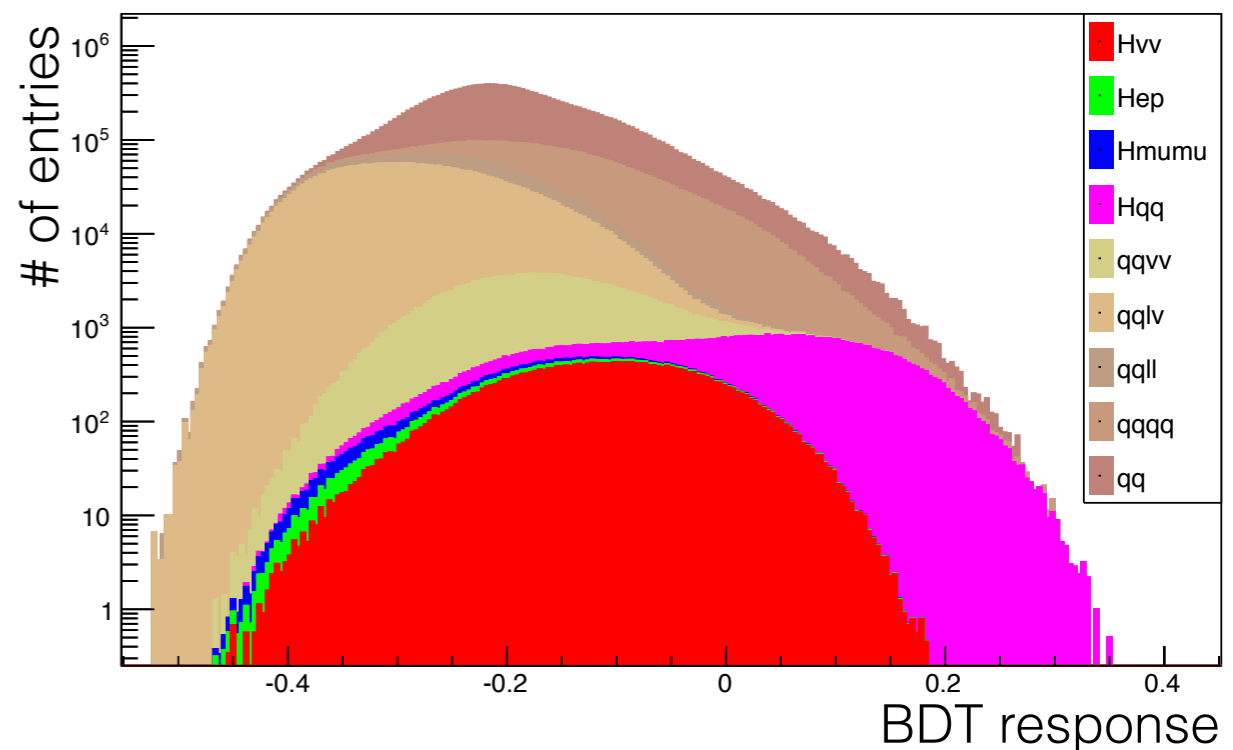
## BDT ranking:

- 1)  $M_H$ ,
- 2) thrust,
- 3)  $E_{\text{reco}}$ ,
- 4)  $\theta_H$ ,
- 5)  $P_T$ ,
- 6)  $\phi_H$

- 1)  $N_P$
- 2)  $P_{\text{max}}$
- 3) thrust
- 4)  $\cos \theta_{\text{thr}}$
- 5)  $\theta_{ij}$
- 6)  $M_Z$



$HZ: Z \rightarrow \text{jets}$

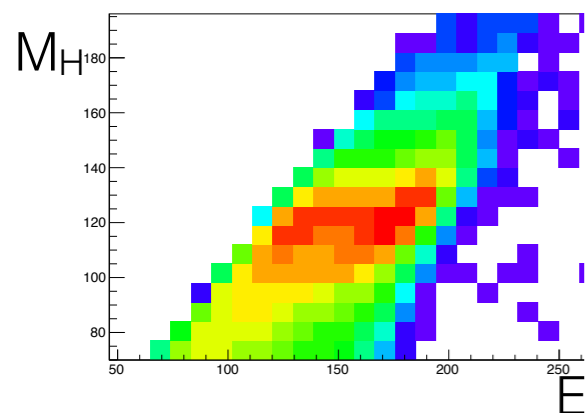


# BDT Performance

Preselection:

$H\nu\nu$

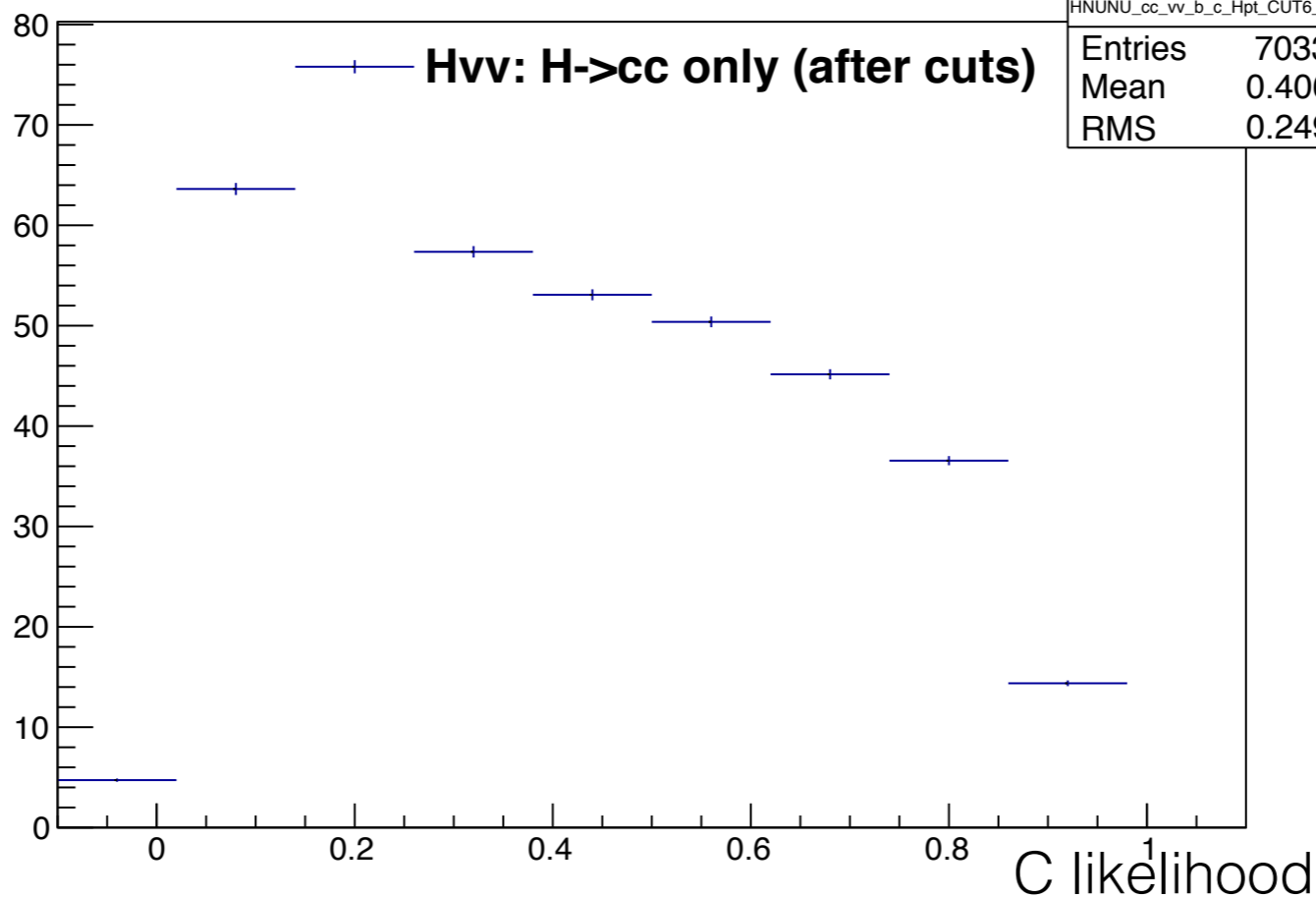
- $80 < M_H < 180$
- $60 < E_{\text{reco}} < 250$



BD

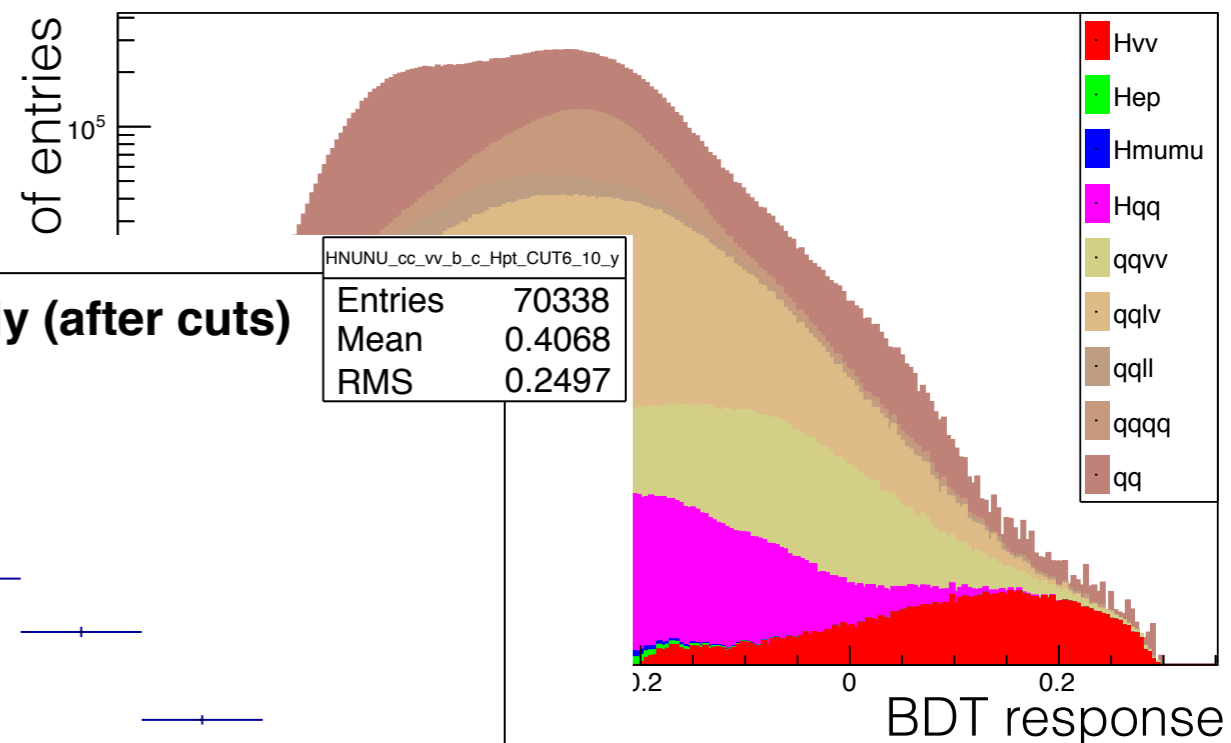
- 1)  $M_H$ ,
- 2) thrust,
- 3)  $E_{\text{reco}}$ ,
- 4)  $\theta_H$ ,
- 5)  $P_T$ ,
- 6)  $\phi_H$

HZ:  $Z \rightarrow \text{jets}$

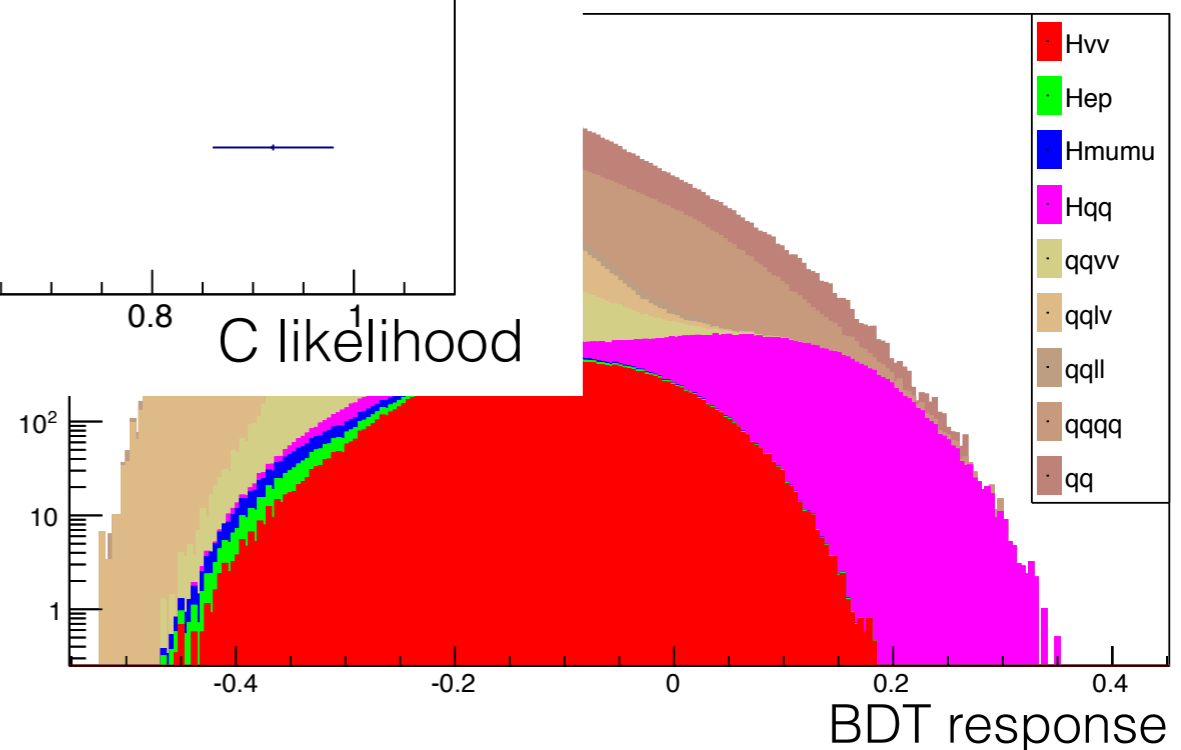


- 3) thrust
- 4)  $\cos \theta_{\text{thr}}$
- 5)  $\theta_{ij}$
- 6)  $M_Z$

$H\nu\nu$



$\rightarrow \text{jets}$



# Efficiency Improvements

Hvv cutflow	bb	cc	gg	qq	qqlv	qqvv
nocuts	14456	729	2185	$1.2 \times 10^7$	$2.95 \times 10^6$	162300
$60 < E_{\text{Reco}} < 260$	14449	728	2183	$9.1 \times 10^6$	$1.6 \times 10^6$	158484
$80 < H_M < 180$	14174	714	2147	$6.9 \times 10^6$	741522	129504
BDT (Hqq) $< 0.07$	14173	714	2147	$6.9 \times 10^6$	741522	129504
BDT (Hvv) $> 0.11$	8773	401	1071	4621	1975	1843
Total Efficiency	61%	55%	50%	$3.7 \times 10^{-4}$	$6.6 \times 10^{-4}$	1.1%

Hqq cutflow	bb	cc	gg	qq	qqqq
nocuts	26209	1322	3961	$1.2 \times 10^7$	$2.8 \times 10^6$
$50 < Z_M < 130$	25621	1294	3869	$1.5 \times 10^6$	$2.7 \times 10^6$
$70 < H_M < 200$	25615	1293	3869	$1.37 \times 10^6$	$2.7 \times 10^6$
BDT (Hvv) $< 0.08$	25338	1288	3859	$1.37 \times 10^6$	$2.7 \times 10^6$
BDT (Hqq) $> 0.11$	13434	566	1630	49994	2912
Total Efficiency	51%	43%	41%	$3.9 \times 10^{-3}$	0.1%

# Template Fit

- Binned maximum likelihood fit on multi-dimensional space: b and c likelihoods and  $H_{Pt}$
- Assume Poissonian fluctuation for each data bin:

$$P_{ijk} = \frac{\mu^n e^{-\mu}}{n!}$$

with  $n$  = number of data entries in bin  $ijk$   
and  $\mu = \sum w_m T_m$  for the same bin

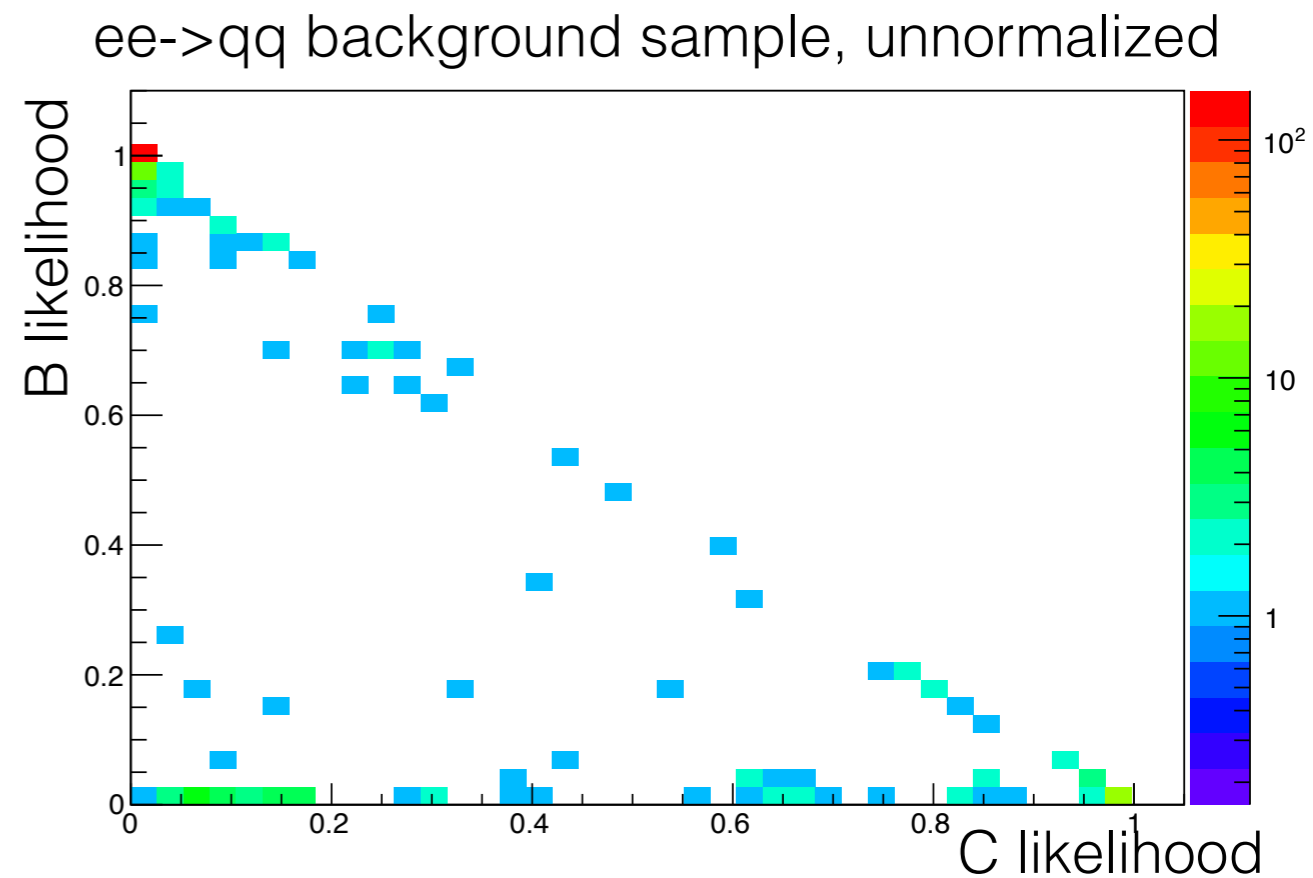
- Then the Likelihood is the product of  $P_{ijk}$  in all bins
- Find the  $w_m$  that maximize this value



# Fit Methods

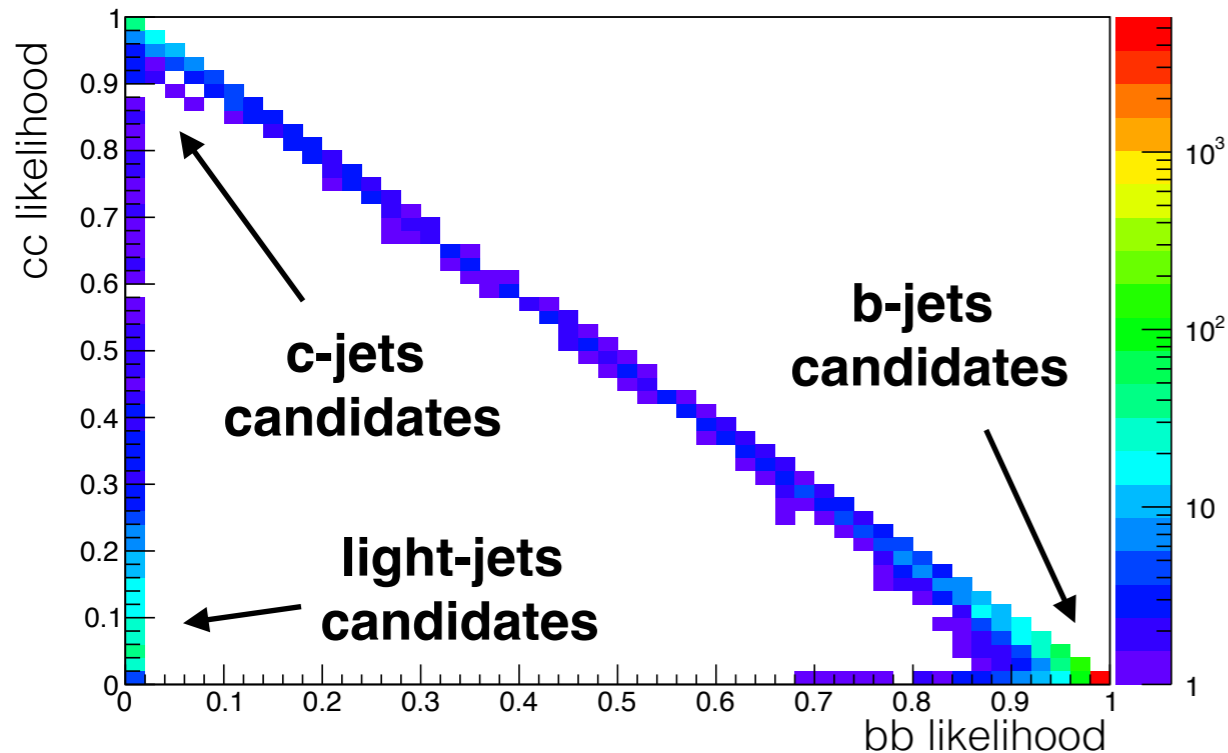
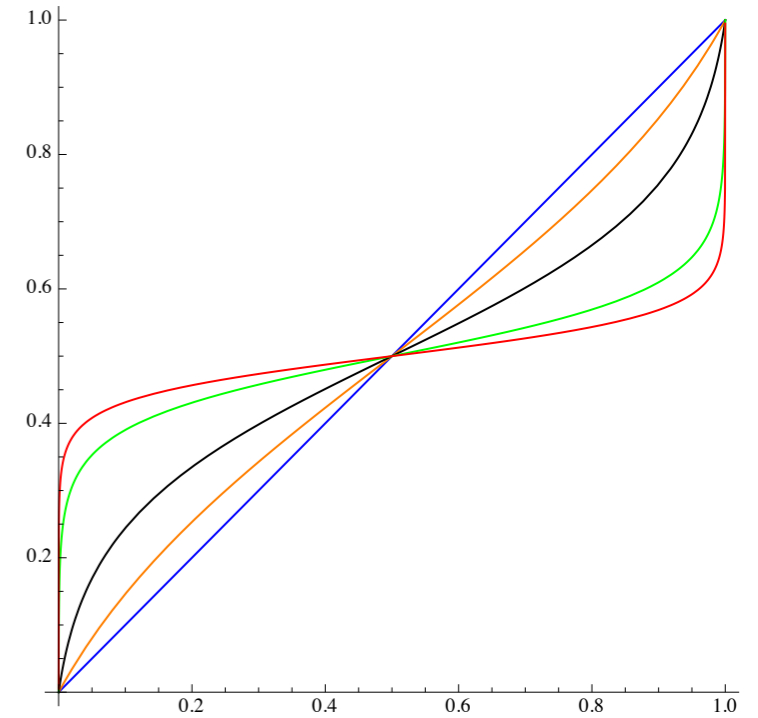
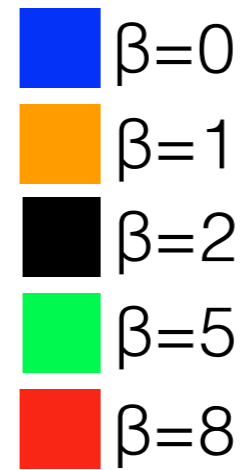
1. Log likelihood in 3D space (b-like, c-like and Hpt)
2. Log likelihood in multiple 1D projections
3. MCMC in multiple 1D projections (BAT toolkit)

- All give similar results for coarse binning ( $\sim 10\text{-}12\%$  in  $H_{VV}:H\rightarrow cc$ ), only 3D Log likelihood gets better with finer binning, probably due to template artifacts



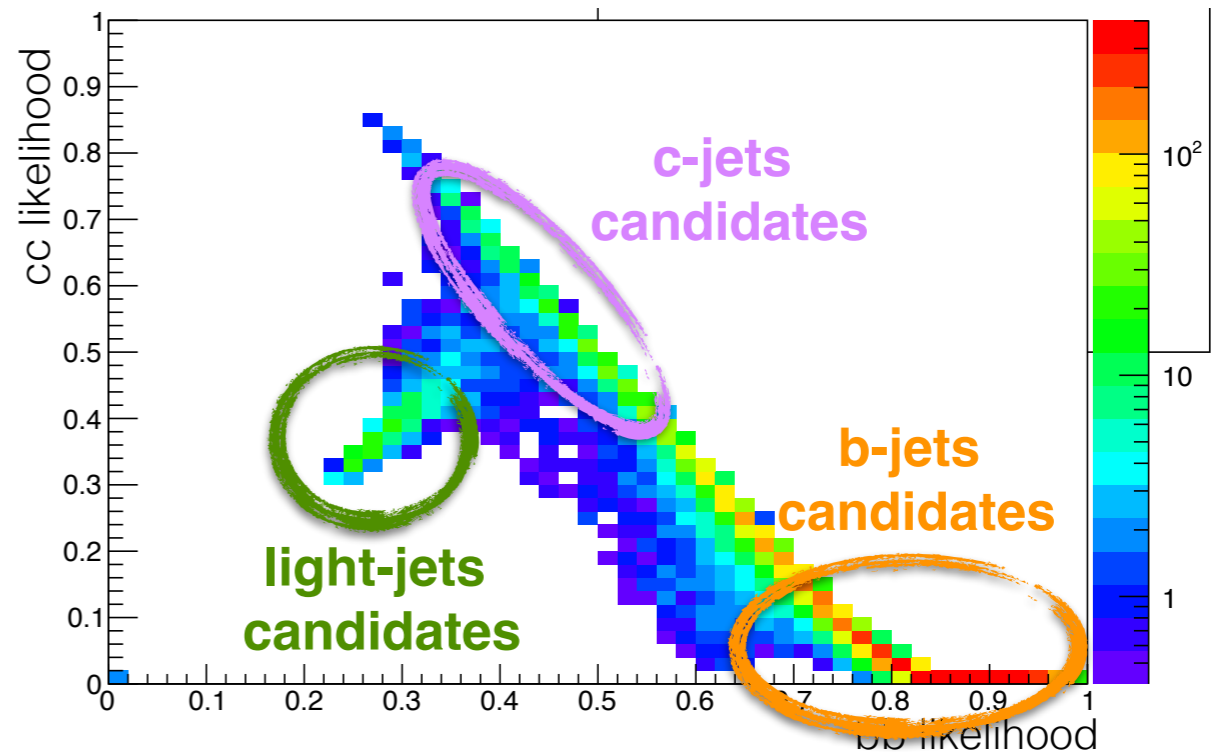
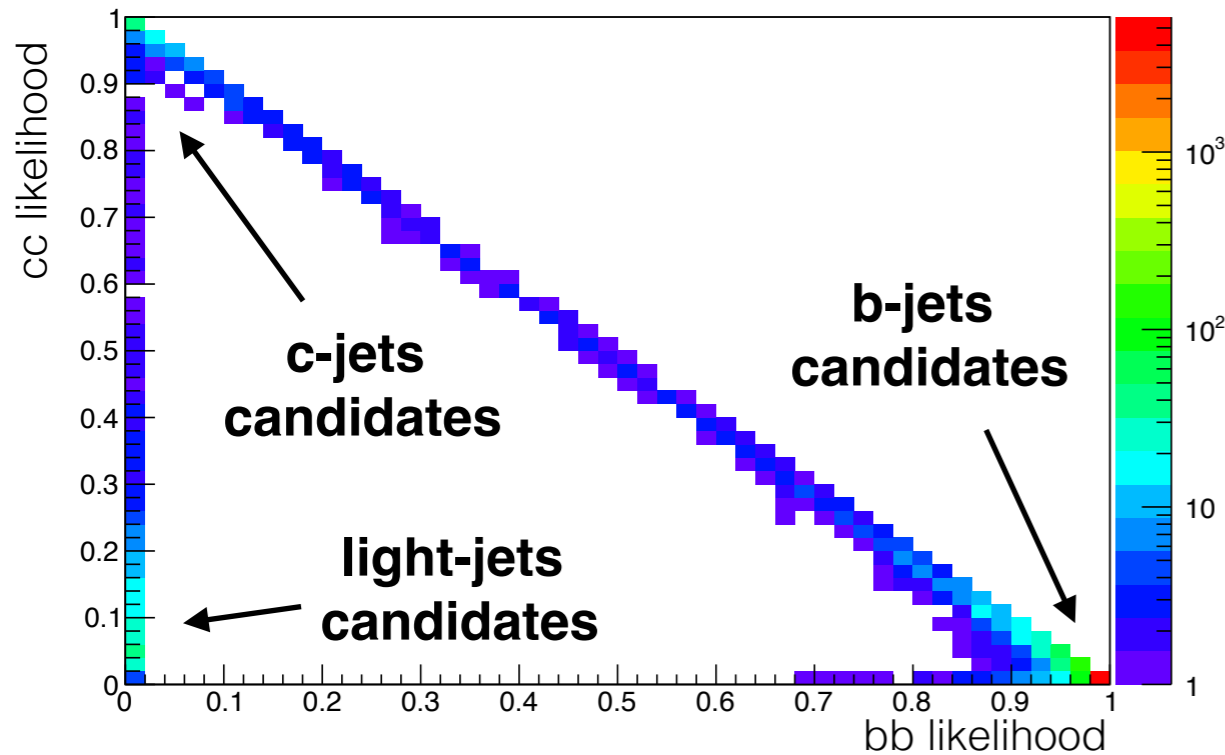
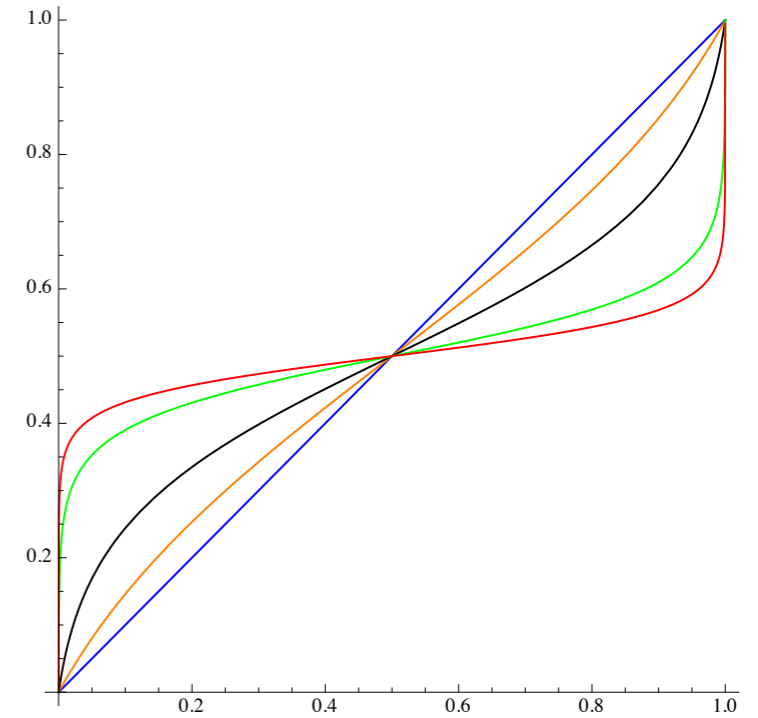
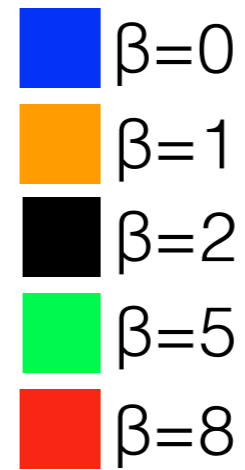
# Remapping the Flavor Space

$$f(x, \beta) = \frac{\tanh^{-1}((2x-1) \tanh(\beta)) + \beta}{2\beta}$$

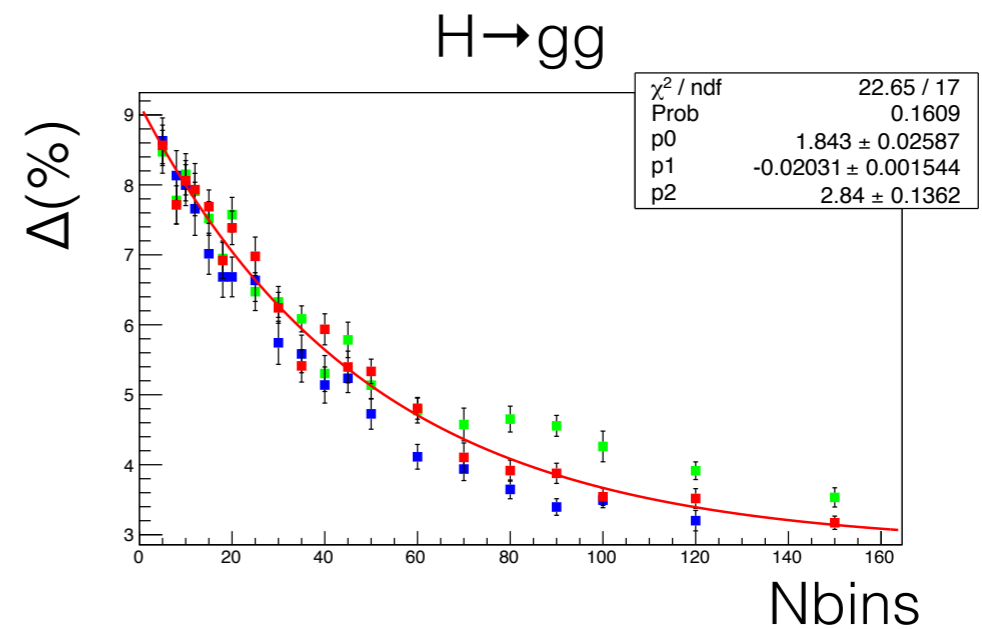
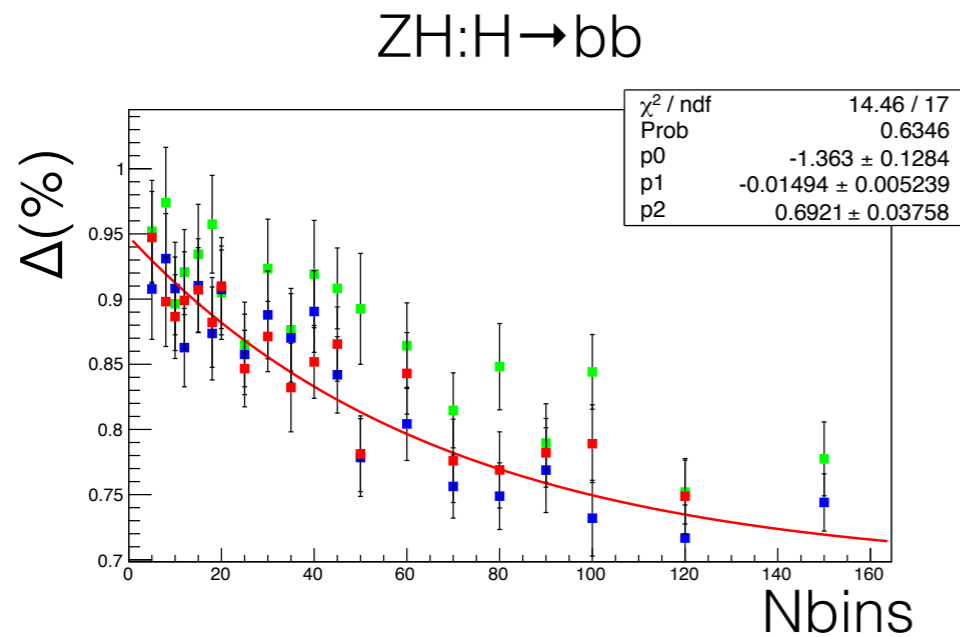
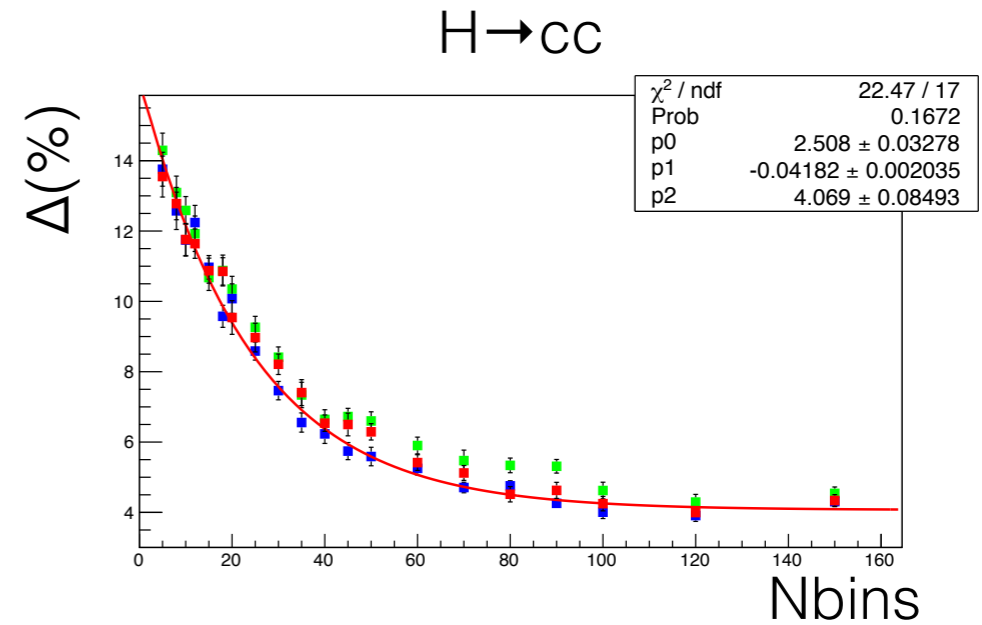
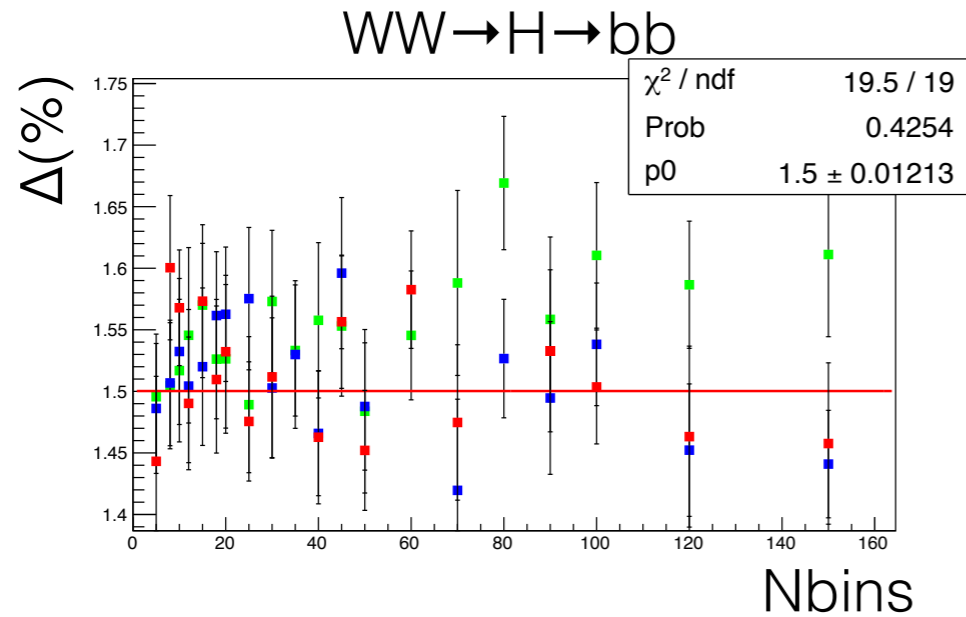


# Remapping the Flavor Space

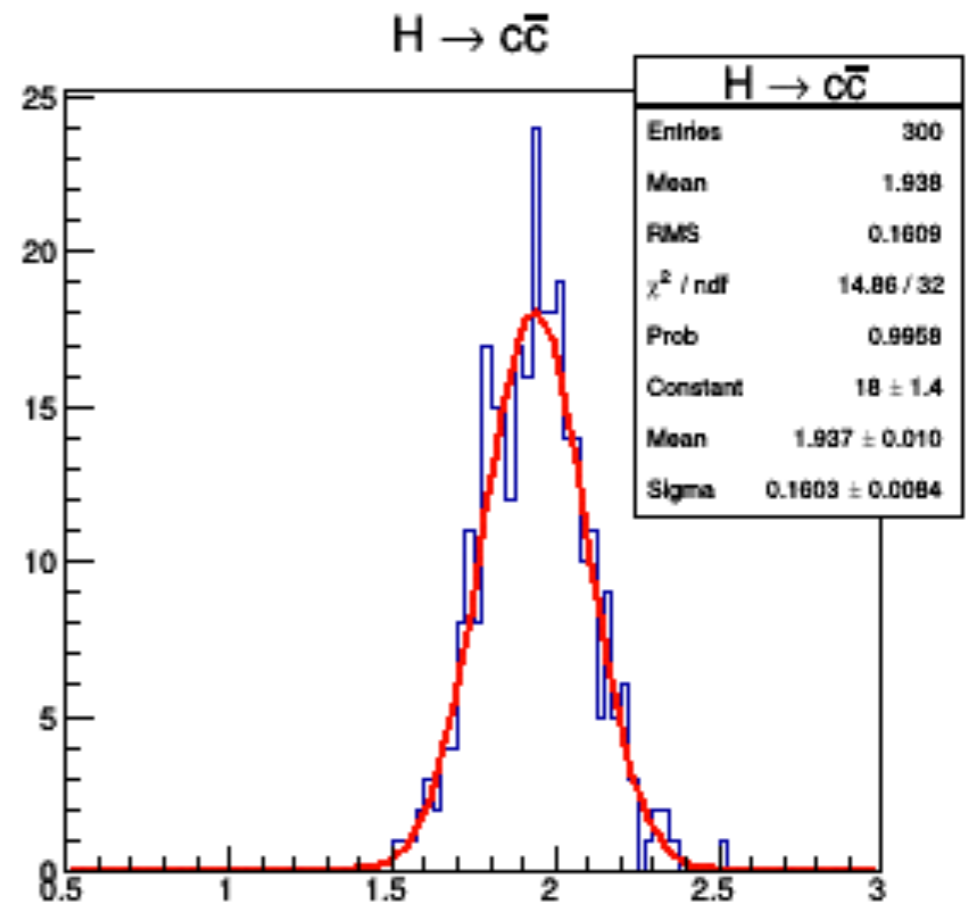
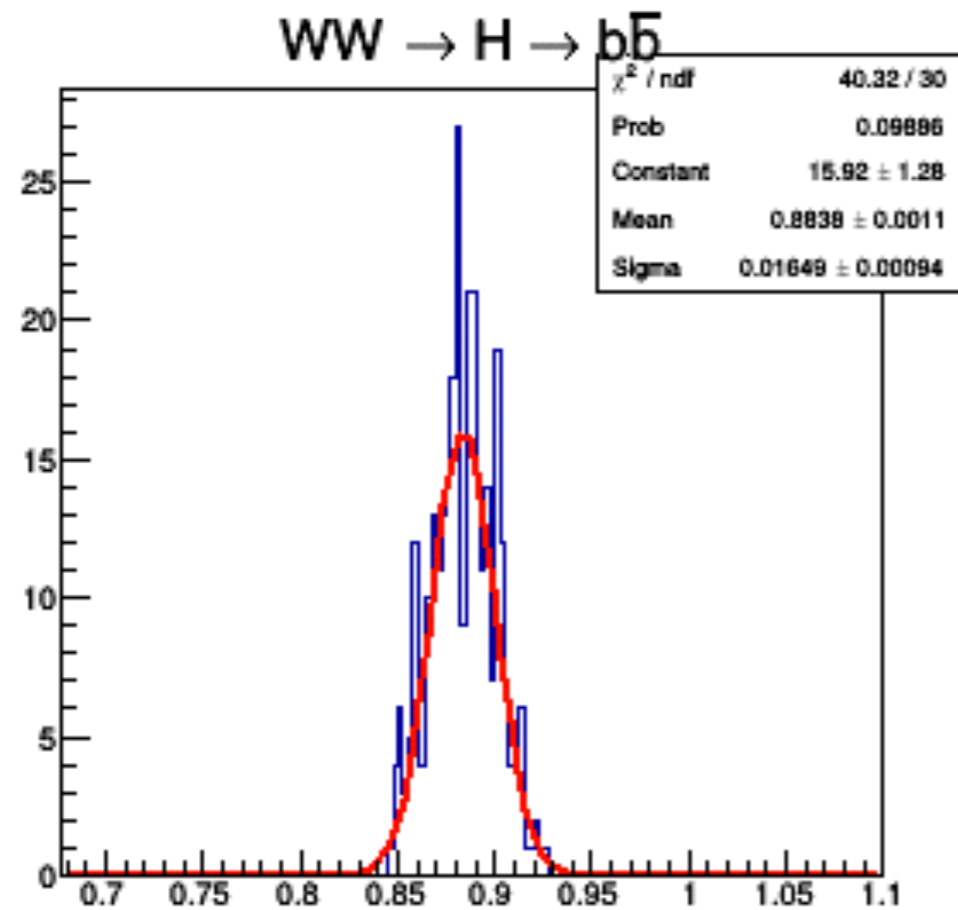
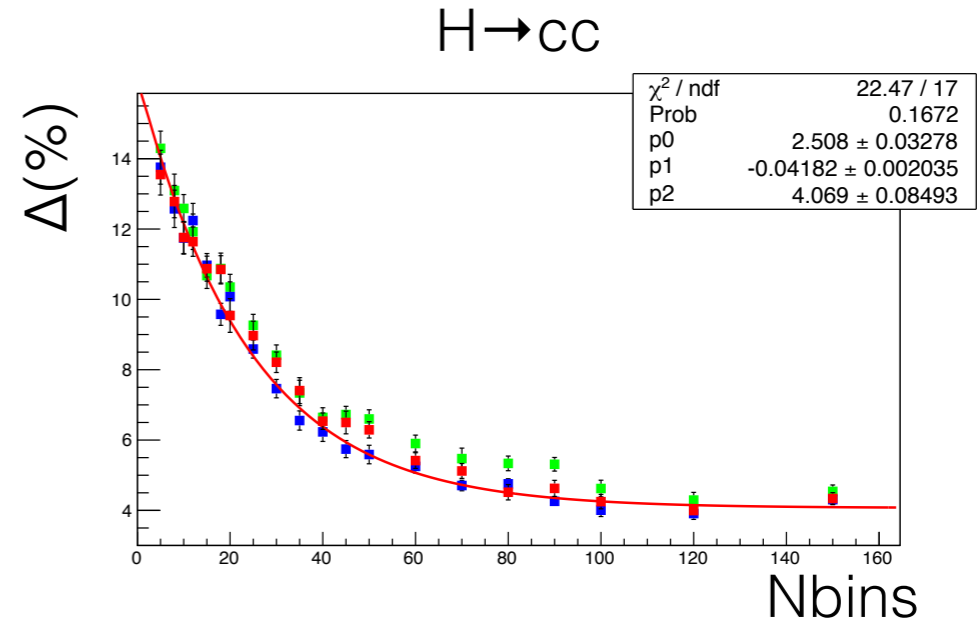
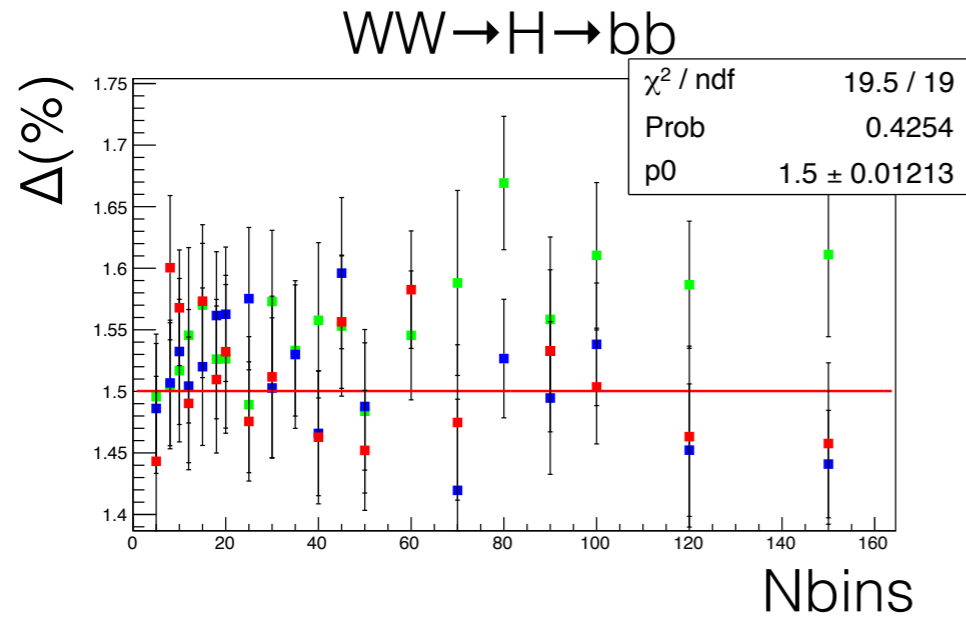
$$f(x, \beta) = \frac{\tanh^{-1}((2x-1) \tanh(\beta)) + \beta}{2\beta}$$



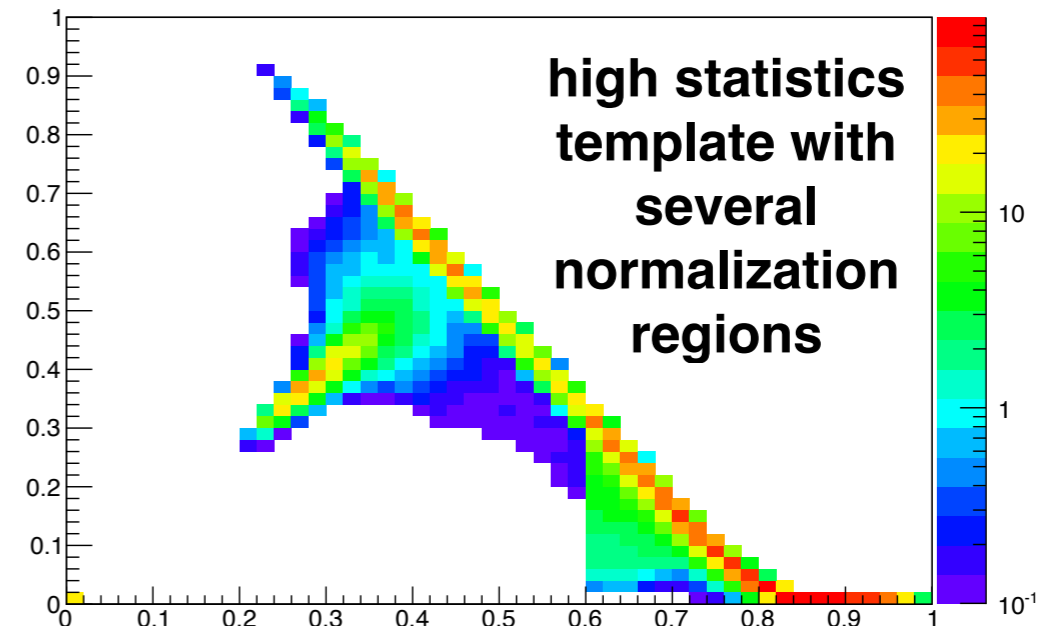
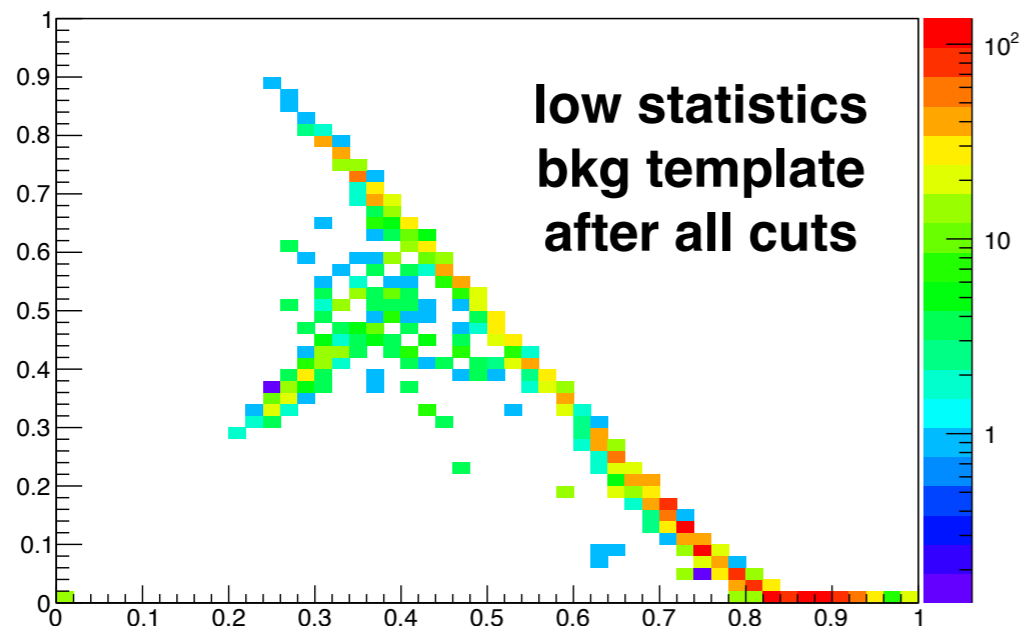
# Remapping Results



# Remapping Results



# Modeling the background



- Using the “mockup” background increase the uncertainty of H branching considerably, BUT it is very difficult to segment the space and normalize since the “cliffs” are very close to the H- $\rightarrow$ cc signal region
- Using dedicated Z- $\rightarrow$ qq background samples to produce a high-statistics template with the right shape also reduces precision
- Smearing the histogram with smoothing functions

# Conclusions

- Selection efficiency has increased drastically thanks to better training statistics for  $H \rightarrow cc$  and  $H \rightarrow gg$
- Analysis now fully implements both  $H_{VV}$  and  $H_{qq}$  cutflow and performs a simultaneous fit of the templates of both
- Uncertainty on  $cc$  did not scale linearly with improved efficiency (as would be expected from background-driven data sample)  
The shape of the flavor space seems to have changed a lot